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The Impact of Vacant, Tax-Delinquent, and Foreclosed Property on Sales Prices of Neighboring Homes

Stephan Whitaker and Thomas J. Fitzpatrick IV

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In this empirical analysis, we estimate the impact of vacancy, neglect associated with material property-tax delinquency, and foreclosures on the value of neighboring homes using parcel-level observations. Numerous studies have estimated the impact of foreclosures on neighboring properties, and these papers theorize that the foreclosure impact works partially through creating vacant and neglected homes. To our knowledge, this is only the second attempt to estimate the impact of vacancy itself and the first to estimate the impact of tax-delinquent properties on neighboring home sales. We link vacancy observations from Postal Service data with property-tax delinquency and sales data from Cuyahoga County (the county encompassing Cleveland, Ohio). We estimate hedonic price models with corrections for spatial autocorrelation. We find that an additional property within 500 feet that is vacant, delinquent or both reduces the home's selling price by at least 1.4 percent. The impacts of foreclosed homes are revealed when the data are disaggregated by the poverty level or vacancy level of the census tract. In low-poverty areas, tax-current foreclosed homes (vacant or occupied) have large negative impacts of approximately 4 percent. In models estimated on high-poverty and high-vacancy subsets of the data, we observe positive correlations of sale prices with tax-current foreclosures and negative correlations with tax-delinquent foreclosures. These results are only marginally significant, but they may reflect selective foreclosing on better-maintained properties or better maintenance by tax-paying foreclosure auction winners. The marginal medium-poverty and medium-vacancy census tracts display the largest negative responses to vacancy and delinquency in nearby nonforeclosed homes. These results suggest that federal housing policy's expansionary focus may be problematic in less-robust housing markets by contributing to the oversupply of housing.

JEL codes: R31, R32, R38, R58, C31, R23.

Keywords: foreclosure, vacancy, abandonment, residential property, home prices, spatial modeling, low-value property, distressed property.

*Originally posted in September 2011. In the original version of this working paper, the status of the sold property itself was included in the distress counts. We did not intend to include it because this erroneously attributes part of the foreclosure discount of the property itself to a neighboring foreclosure. This version corrects the counts. The estimated impact of foreclosures and multiple-distress homes is much lower and the estimated impact of vacant or delinquent homes is higher.

Stephan Whitaker is at the Federal Reserve Bank of Cleveland and can be reached at stephan.whitaker@clev.frb.org. Thomas J. Fitzpatrick IV is at the Federal Reserve Bank of Cleveland and can be reached at thomas.j.fitzpatrick@clev.frb.org. The authors would like to thank Mary Zenker for her extensive research assistance on this project and Kyle Fee and Carole Ouedraogo for their additional help. They are grateful to Michael Schramm for bringing the vacancy data to their attention and to Lisa Nelson for sharing her list of institutional market participants. They also appreciate all the useful comments we received from seminar participants at Cleveland State University, The Ohio State University, the REO workshop hosted by the Federal Reserve Bank of Cleveland and Cleveland State university, and the Ohio Conference of Community Development's 2011 Annual Meeting.

1 Introduction

Recent events in housing markets are attracting much scholarly attention to foreclosures. One line of research that is developing rapidly focuses on the externalities associated with foreclosure, primarily a foreclosed home's impact on surrounding properties. There are two general deficiencies with this line of research: the nearly exclusive focus on robust housing markets, and the assumption that foreclosures themselves, rather than factors correlated with foreclosure, drive down surrounding housing prices. This paper attempts to fill the gaps in prior research in two ways. First, it focuses upon a less robust housing market: Cuyahoga County, Ohio (home to Cleveland). Second, it incorporates parcel-level vacancy and real property tax delinquency (as a measure of neglect) in addition to foreclosure.

Foreclosure, vacancy, and tax delinquency differ in important ways, though they may all lower surrounding home values or indicate distress that lowers home values. Foreclosure occurs when a debtor fails to pay a debt secured by the debtor's home, and the creditor opts to seize and sell the property instead of continuing to seek payment from the debtor. During foreclosure, homeowners have little incentive to maintain their homes, as every dollar put into upkeep or improvements will primarily benefit the foreclosing lender.[1] Thus, recently foreclosed homes are more likely to be distressed due to deferred maintenance than homes that have not recently been through a foreclosure. Additionally, foreclosure adds a unit of supply to a local housing market. Assuming a competitive housing market, this additional supply should put downward pressure on home values. Finally, foreclosure may lower surrounding home values when they are used as

[1] In states that allow deficiency judgments, where the lender can pursue borrowers for the difference between the amount owed on the loan and the price paid for the home at foreclosure auction, homeowners may have more of an incentive to actively maintain homes. Historically, however, deficiency judgments are not commonly pursued for many reasons. For example, homeowners who have gone through foreclosure rarely have the ability to repay a deficiency judgment, and such judgments are more easily dischargeable in bankruptcy than secured debt.

comparable properties by real estate appraisers or realtors to price non-foreclosed real estate. In light of the volume of properties recently moving through REO (real estate owned), lenders lower the sales prices of homes they own in order to sell them quickly, because the carrying costs of vacant properties are high. When appraisers or realtors determine the value of a home, they may select foreclosed homes as comparable properties without considering the eagerness of the seller.[2]

Vacancy is closely related to foreclosure, but distinct in important ways. A home that has been foreclosed upon will be vacant immediately after the foreclosure but the vacancy may be temporary, as the property is auctioned off to a new owner or to a bank or investor who usually attempts to find a new owner.[3] Vacancy is distinct from foreclosure in that a property is vacant when it is not being occupied, which is not a result of a foreclosure in the vast majority of cases (there are seven times more vacancies than foreclosures in our data).[4] Vacancy lowers surrounding property values in ways that closely resemble foreclosure. Each vacancy is another likely unit of supply on the market, which should put downward pressure on home values. Vacant properties are usually not maintained as well as occupied properties because no one is present on a daily basis to care for them. While they may be cared for by an owner living elsewhere, there is less incentive and opportunity to maintain them as often and as carefully as an owner-occupier would. This problem is exacerbated

[2]Real estate appraisal guidelines allow for some discretion when selecting comparable properties. See, e.g. Uniform Standards of Professional Appraisal Practice 2010-2011, Standards 1 & 2, available at http://www.uspap.org/USPAP/frwrd/uspap_toc.htm. Thus, foreclosure liquidations and REO sales may not be used when selecting comparable properties.

[3]Not all purchasers at foreclosure auctions seek to quickly fill the home. Some spend time rehabilitating it or marketing it to other property investors. (Ergungor and Fitzpatrick 2011) Some homes remain vacant for years after a foreclosure, especially high-poverty areas. (Whitaker 2011)

[4]We consider a property vacant if it is not legally occupied. In some sense this may over-count vacancies, as some may be occupied by squatters. But such occupants have little incentive to maintain, and virtually no incentive to improve, the property.

with long-term vacancy, which occurs naturally in less robust housing markets where there may not be sufficient demand to reoccupy vacant houses, and in colder-weather climates where a single winter can cause significant damage to a property that is not attentively maintained.

While vacancy and foreclosure intuitively put downward pressure on home values through supply and disamenity channels, real property-tax delinquency does not: it neither immediately creates additional supply nor is it easily observable by neighborhood residents.[5] Yet, certain levels of tax delinquency may signal the abandonment of property by its owner, because once a property becomes tax delinquent it may be taken from the owner through tax foreclosure. Property is abandoned at the point that property owners and inhabitants stop investing in the property with the intent of foregoing their ownership interests. Abandonment usually occurs when a property's carrying, operating, or rehabilitation costs are too high relative to the property's value. The condition of abandoned property deteriorates rapidly, as there is no one maintaining or improving it. The decision to abandon property is made subjectively, and cannot be directly observed. This has led previous researchers to use subjective municipal determinations of whether a property has been abandoned (Mikelbank 2008). While the subjective assessments are not reproducible, these studies show that when the impact of foreclosed property on surrounding home values is not considered alongside vacant and abandoned property, it overstates the impact of foreclosure. We use combinations of reproducible, objective indicators as proxies for abandonment. If we find these indicators are informative, they may be a substitute for this difficult-to-measure status.

In the years following the rapid decline in housing values, hedonic price modeling has been applied to evaluate the impact of properties that have been through a foreclosure. Foreclosure sales are easily identified in county recorder or court records, so many panel studies have been conducted

[5]A tax delinquency becomes a unit of supply if it is eventually subject to tax foreclosure. A tax-delinquent home might be on the market if the financially-distressed owner is trying to get out of an unsustainable financial situation.

on the impact of foreclosures. Often these studies are motivated by suggesting the foreclosed properties are often vacant, abandoned, and blighted. However, foreclosure is a noisy measure of the impact of vacancy and abandonment. A few of the studies have incorporated the impact of vacancy and abandonment but this has been limited by the unavailability of parcel-level vacancy data (Mikelbank 2008, Hartley 2010). With data on vacancy, foreclosure, and tax-delinquency, we can begin to disentangle the impact of each status on the value of neighboring properties.

In order to better understand these dynamics, this analysis is the first application of hedonic price modeling to a panel data set, specifically representing vacancy and property-tax delinquency of residential properties. To the authors' knowledge, this is the first study to use property-tax delinquency as an objective indicator of abandonment. This study is the first to use the U.S. Postal Service's (USPS) administrative records of vacancy to identify vacant properties at the address level. The records are commercially available on a monthly basis, so homes can be observed moving into and out of vacancy. Also, the time variation in the data gives us both increased accuracy in the count of nearby vacant homes at the time of the sale, and it creates additional variation in the vacancy counts within neighborhoods. Focusing on within-neighborhood variation addresses some of the endogeneity issues that always challenge hedonic price analyses. We find that when foreclosure, vacancy, and property-tax delinquency are all included, the impact of foreclosure on surrounding home values is greatly reduced.

The rest of the paper proceeds in five sections. In the remainder of this section we review the relevant literature. In section two, we discuss the theory behind our modeling. In section three we discuss the data we use and provide descriptive statistics. In section four we discuss our results, and in section five we conclude and discuss policy implications of our findings.

1.1 Literature

Since housing prices cooled in 2007, policymakers are increasingly aware of the external costs of foreclosure, vacancy, and abandonment. Research has intensified over the past few years, but it primarily focuses upon foreclosure. While foreclosure may lower surrounding home values, vacancy and abandonment have long been recognized by practitioners as more important roadblocks to revitalizing distressed neighborhoods. Interest in vacancy and abandonment dates to well before the current crisis. For example, one early paper developed a theoretical model based upon New York City housing markets that approximated that owners would abandon property when the current level of rents in the neighborhood did not justify the rebuilding or renovation of a distressed property (White 1986). Yet this research has rarely made an attempt to quantify the impact of vacancy and abandonment on surrounding home values.

One gap in research on abandoned properties is the lack of a universal definition of "abandonment." Municipalities tend to use a period of vacancy as a proxy for abandoned structures, but the period they must be vacant to become abandoned varies widely (Pagano and Bowman 2000). A structure is generally considered abandoned when it is chronically vacant, uninhabitable, and the owner is taking no steps to improve the property (Cohen 2001). Unfortunately, to determine that a property is uninhabitable or in disrepair researchers rely upon an assessment from the municipality itself, obtained through inspections (Cohen 2001, Mikelbank 2008). This data is often incomplete, because municipalities lack the resources to frequently survey all properties within their jurisdiction (Pagano and Bowman 2000). These inconsistent definitions make it impossible to accurately compare results across cities.

For the purposes of this study, we use vacancy, tax delinquency, and their coincidence as measures of distress and abandonment. Vacancy is nearly universal among abandoned properties, as by definition they are not being cared for by either owners or inhabitants. Tax delinquency has been referred to as "the most significant common denominator among vacant and abandoned properties," (Alexander 2005), and correlations exist between tax-delinquency rates and decreases in home sales prices in greater Cleveland (Simons, Quercia, and Maric 1998). This is logical, as owners who plan to retain ownership either pay property taxes or run the risk of losing the property in a tax foreclosure. Property owners with no interest in retaining ownership have no incentive to pay property taxes. Owners with no interest in retaining ownership also have no incentive to maintain their property, so where we find property tax delinquency we would expect to find deferred maintenance.

Research ties widespread vacancy and abandonment to long-term population decline. The process of filtering, where the occupation of new, high quality residential construction results in old, low-quality residential vacancy has been analyzed for decades (Lowry 1960). Cities that self-report the largest supply of abandoned housing have experienced persistent population loss, suggesting that abandonment occurs in the later stages of a neighborhood's lifecycle (Cohen 2001). When building permits outpace household growth in a metropolitan area, filtering causes increased vacancy and abandonment in the city's urban core and inner-ring suburbs (Bier and Post 2003). The durable nature of housing results in a very slow adjustment of the housing stock to match the smaller population (Glaeser and Gyourko 2005). The lag manifests itself in vacancy and abandonment. Abandoned property is a significant, long-term problem in older industrial cities that have experienced outmigration from their urban cores, but such filtering also leads to some abandonment in cities with generally robust housing markets.

Until recently, most research on the impact of urban decline has focused on foreclosures in robust housing markets. The most commonly cited study on the topic estimates that each mortgage foreclosure within one eighth of a mile (660 feet) of a single-family home lowered its value by about one percent, based on one year of home sales data from Chicago in the late 1990s (Immergluck and Smith 2006). In order to determine whether foreclosures create significant price declines to surrounding property or are simply a result of local housing trends, Harding, Rosenblatt and Yao examine the impact of nearby foreclosures on home sales in select zip codes across seven metropolitan areas over nearly 20 years, and factor in local price trends (2009).[6] They find that above local housing price trends, each foreclosure within 300 feet lowers a home's value by up to one percent, and each foreclosure from 300-500 feet lowers a home's value by about one half of one percent.

Schuetz, Been and Ellen control for home prices prior to foreclosures and investigate the linearity of the relationship between the number of foreclosures and price discount on surrounding homes (2008). Using data from New York City from multiple years, they find that foreclosures within 250 feet of a home reduce its value by one to two percent. Outside of the 250 foot ring, a larger number of foreclosures is necessary to impact a home's value: three or more from 250-500 feet lowers a home's value by one to three percent, and six or more from 500-1000 feet lower a home's value by about three percent.

Campbell, Giglio and Pathak look more broadly at the impact of forced sales on home prices. They define forced sales as those resulting from bankruptcy, death, and foreclosure (2011). Looking at housing data for Massachusetts over 20 years, they find that forced sales due to foreclosure have much steeper price discounts than those due to bankruptcy or death. Controlling for the average level of voluntary sales prices, they find that a foreclosure within a twentieth of a mile (264 feet) lowers the value of a home by about 1 percent, and the closer the foreclosure to the home the larger the discount.

Lin, Rosenblatt and Yao (2009) attempt to better understand why foreclosures lower surrounding home values. They used a theoretical model for home pricing using comparable properties,

[6] The seven MSAs are Atlanta, Charlotte, Columbus, Las Vegas, Los Angeles, Memphis and St. Louis.

attempting to reproduce the effects of appraisers and realtors. They estimated that in Chicago, each foreclosure liquidation can depress short-run property values of homes within a half mile as much as 8.7 percent in down markets and 5 percent in up markets.[7]

Only two studies look beyond foreclosure and incorporate vacancy into their analysis. One uses vacancy rates to classify neighborhoods into broad categories. Hartley attempts to delineate between the "supply" and "disamenity" effects of foreclosures to determine how much of the price discount was due to each (2010). By looking at different types of foreclosed property in Chicago, Hartley decomposes the effects of foreclosure on nearby housing in census tracts with low and high vacancy rates. The explicit assumption in Hartley's work is that renter-occupied multi-family buildings are not substitutes for single-family homes, so a renter-occupied multi-family building foreclosure will not change the potential housing supply for persons seeking a single-family home, and vice versa. In census tracts with low vacancy rates, he finds that each foreclosed single-family home within 250 feet reduces a home's value by 1.6 percent due to an increase in supply, while the disamenity effect of the foreclosed home is near zero. In census tracts with high vacancy rates, he estimates the disamenity effect of a foreclosed multi-family home lowers surrounding property values by about two percent, while the supply effect is near zero.

One issue common to all of these studies is that they all acknowledge foreclosures likely lower surrounding home values by becoming disamenities or adding supply to the market, but fail to distinguish between foreclosures that are reoccupied quickly, foreclosures that sit vacant and are well maintained, and those that become abandoned. Hartley's results hint at the importance of this distinction by illustrating that neighborhood property values are lowered due to supply or disamenity, depending on the location (and likely the condition) of the property. Understanding

[7] This model assumed that foreclosure liquidations of comparable properties are used by realtors when pricing a home. Anecdotally, realtors and appraisers in less robust housing markets report ignoring foreclosure liquidations when pricing comparable properties unless there are no other reasonable comparisons.

the difference between foreclosed, vacant, and abandoned property is critical for policymakers who seek to understand how to address these issues. Mikelbank illustrates that estimating the impact of either vacant and abandoned property or residential foreclosures in isolation overstates the impact of both, based upon his empirical analysis of one year of housing sales in Columbus, Ohio (2008). In this paper, we elaborate on Mikelbank's study, focusing on the housing transactions in Cuyahoga County, Ohio, in an attempt to better understand the interplay between foreclosures, vacancies, abandoned properties and surrounding home values.

2 Theory

The methods we will employ are based in the vast field of hedonic models of real estate pricing. Origination of these models is generally credited to Rosen (1974). In their simplest application, the sales price of a home is regressed on indicators of the home's characteristics, and the coefficients are interpreted as the marginal prices of those characteristics (see equation 1). P_i is a home sale price. z_{ij} are characteristics of the home and its location.

$$P_i = \alpha + \sum_{j=1}^{J} \beta_j z_{ij} + \varepsilon_i \tag{1}$$

The HP model relies on some standard assumption which, nevertheless, could be violated in reality. It assumes the housing market is competitive and that both buyers and sellers are fully informed.[8] Using a linear specification suggests that the characteristics of the home can be costlessly repackaged. This is obviously not the case, so most applications employ a semi-log specification that implicitly interacts all the characteristic measures. In this specification, the coefficients cannot be

[8] A significant number of homes in Cuyahoga County have been purchased by out-of-state investors over the internet. Homes are also purchased out of REO inventory blindly as part of a bulk sale at a pre-negotiated price. Full information is doubtful in these cases.

interpreted as prices, but rather percentage changes in the price.

$$ln(P_i) = \alpha + \sum_{j=1}^{J} \beta_j z_{ij} + \varepsilon_i \quad (2)$$

Despite including a set of measures of the area surrounding an observed house sale, researchers generally suspect that there are important unobserved location factors. These include amenities and disamenities the researchers has not controlled for (the possibilities are endless). The impact of these factors is also thought to vary with distance. A home closer to the amenity or disamenity will have a larger price response. Omitting a distance-weighted indicator of the factor leaves its influence in the error term. Equation 3 is a hedonic price model that gives two options to address this (Anselin 1988).

$$P = \lambda W_1 P + ZB + \varepsilon \quad (3)$$

$$\varepsilon = \rho W_2 \varepsilon + \mu \quad (4)$$

$$\mu \sim N(0, \sigma^2 I) \quad (5)$$

Equations 1 and 2 used summation notation to emphasize the contribution of multiple characteristics to the sale price. We switch to matrix notation (following the literature) here because the spatial models center on a spatial weight matrix. W_1 is a spatial weighting matrix that gives large weight to the prices of nearby homes and small weight to the prices of far away homes. Multiplying the price vector (P) by W_1 creates a vector of weighted averages of nearby home prices. Including these averages as a control removes the gradient between high price and low price neighborhoods.[9] The remaining variation within neighborhoods tells us approximately how much sale prices would change if we could add or remove distressed properties. λ relates the distance-weighted mean selling price of the other homes to the specific observation. If λ is significant and non-zero, the prices

[9]The negative correlation between vacancy and price is very obvious in maps (figures 2 and 1), but it is not the relationship we are attempting to estimate.

are said to be spatially dependent. W_2 is also a distance weighting, but in this case relating the errors of the observations to one another through ρ. A non-zero ρ indicates spatial error correlation, which would be caused by unobserved amenities and disamenities being in the error terms of nearby homes. μ is the normal error remaining after the spatial error has been modeled. Unfortunately, ρ, λ, W_1, and W_2 cannot all be estimated at once, so researchers usually make some plausible assumption about either the spatial weight matrices or the spatial autocorrelation coefficients, and estimate the other. Both W_1 and W_2 can estimated in the same model, if the theory suggests a specific error structure that differs from the relationship between the prices. In this analysis, we do not have a theoretical reason to use a W_2 different from W_1, and using the same spatial weight matrix can introduce collinearity issues.[10] We will refer to the correction involving W_1 as the spatial lag correction and the correction employing W_2 as the spatial error correction.

Most regional economists and policymakers would agree that a dataset that covers an entire urbanized county, as ours does, represents several separate housing markets, rather than one. For an average buyer, many high-cost neighborhoods would offer no options within their budget constraint. Likewise, high-income buyers would not consider a home of any type or price if it is in a low-performing school district or high-crime neighborhood. When the models are estimated on a pooled data set, the coefficients are an average across all types of buyers. It is useful to know how the impact of a vacant home differs in high-income verses low-income neighborhoods, so we estimate our models on several submarkets.

The specification of our model is motivated by several practical considerations. First we are interested in helping policymakers identify types of distressed homes that have the greatest negative impact on neighboring property values. Therefore, we are dividing the homes into counts based on

[10] We estimated models with slightly different matrices, such as one truncated at one kilometer and the other truncated at two kilometers. In general, adding the second spatial correction did not substantially change the results.

which markers of distress they exhibit, and not allowing them to contribute to multiple counts. In future evaluations of housing market interventions, we want to be able to identify a precise control group that is the most similar to the homes treated by the intervention. Using all vacant homes or all foreclosed homes is too broad. While many papers in the literature use multiple buffers to demonstrate the distance decay of the impacts of a disamenity, we primarily report the impacts within one buffer. We chose the 500 foot buffer based on findings in previous studies that suggest at 500 feet, the impact of a foreclosure is still significant. A smaller buffer will show a larger, highly significant impact, but it misses many of the sales that are treated. We are reporting coefficients for seven counts, which is challenging to interpret. Multiplying the number of coefficients by additional buffers would make the results much more difficult to relay to policymakers and is not justified by the additional information in this situation.

To briefly review, we expect each indicator of distress – vacancy, delinquency, and foreclosure – to be associated with lower sales prices for nearby homes after controlling for prevailing neighborhood prices and observable characteristics. Vacant homes do not contribute to the vibrancy or security of a neighborhood. In many cases, no one is attending to their appearance daily, so grass is mowed less frequently, snow is not cleared, leaves are not raked, etc. Some of this may be offset if the home is on the market and the sellers have invested in "curb appeal" cosmetic improvements. Unless the home is vacant because it is undergoing major renovations, or awaiting a rental tenant, then the home is either a unit on the market or part of the shadow inventory. The shadow inventory consists of homes owned by individuals that want to sell, but are not actively marketing because they are hoping the market will improve. When a single lender owns many delinquent loans secured by properties in close proximity to one another, and in markets where there is relatively weak housing demand, lenders deliberately pace property foreclosures. In either case, these vacant homes (which are often easy to identify in person) signal to buyers that the market is flush with inventory and shadow inventory, and therefore they can bargain for low prices.

The case of delinquency is more subtle. One can reasonably say that it is not visible on the street and very few people look up the tax delinquency status of neighboring homes (they will sooner or later learn the tax status of a home they are purchasing).[11] For homes that only have tax delinquency, we believe it serves as an objective measure of distress for the property. If the homeowner is unwilling or unable to pay their property taxes, which eventually results in tax-foreclosure, it is very likely that they are unable or unwilling to maintain the property. Poor maintenance of neighboring properties is visible to home purchasers if any exterior or landscaping work is needed.

The impact of foreclosure is more direct, and therefore, we might expect it's per unit impact to be larger. With the exception of strategic foreclosures, every household that went through a foreclosure has experienced financial distress. When the homeowner accepts that they will likely or certainly lose the home, they no longer have an incentive to invest anything in maintenance. In our data, foreclosures are indicated after the sheriff sale, so the purchasers may have paid off the property's tax delinquency. If no third party investor bids above the lending institution's auction reserve, the reserve is recorded as the sale price and the lender takes possession of the property. In many cases, these homes are back on the market or being held as shadow inventory by the lender (Whitaker 2011). If the home is sold out of REO, a second transaction has been recorded at a discounted price. The direct link between these foreclosure-related sales and other sales is the comparables or appraisal process. The foreclosed homes will be considered by sellers, purchasers, and lenders in determining the value of a nearby non-foreclosure property.

We make separate counts of each combination of distress because we think homes in different

[11]While we a referring to the data as tax delinquency data, it does include some uncollected code violation and nuisance abatement fines as described in section 3. Since these vary widely between jurisdictions, we attempt to exclude them from the analysis. In many cases, code violations are visible from the street.

stages of the process will have very different impacts on nearby homes. When past studies have estimated the impact of foreclosures, they are rolling together homes that were just auctioned and are bank owned, homes sold out of REO to speculators that are vacant and delinquent, and homes sold to families that have paid the property taxes and occupied the home. Our parcel-level data with all three measures will reveal if it is certain combinations of distress indicators matter more than others.

3 Data

The bulk of the data used in our analysis is an administrative dataset maintained to track property transactions, property-tax delinquency, and assessed values for taxation. These data include a rich set of characteristics on all residences in the county, including square footage, rooms, garages, and building materials. The data are used in property tax assessments and updated triennially and with permit data.[12] We supplement the house characteristic data with measures of the poverty rate and the college attainment rate for each census tract using estimates from the 2005-2009 American Community Surveys.

The fiscal officer also maintains records of all sales with the key elements of dollar amount, date, seller, and purchaser. Data on tax-delinquency is updated semiannually. We use two tax-delinquency files. The first is a list of parcels that were delinquent anytime in 2010, and the second is a list of properties that were delinquent at any time between January and June 2011. The delinquent amount appears in the record along with any payments that have been made toward it, even complete repayments. The dates when the properties enter or exit delinquency are not available, so these data are static within one year or the other. We pulled from the

[12]If a property owner requests a permit to add an addition on their house, for example, the assessor will estimate the increase in the home's value and adjust the property tax bill accordingly.

dataset the properties that have missed a biennial payment by keeping only observations in which the delinquency amount is at least 40 percent of the annual net tax bill. This eliminates minor accounting errors (there are hundreds of delinquencies of a few dollars or cents) and the minor code violations. Housing codes vary widely across jurisdictions in their stringency, enforcement and recording with the county. The Cuyahoga County fiscal officer, like many county departments nationwide, makes tax delinquency data available for download.[13]

One novel dataset that is being used for the first time (to the best of our knowledge) is the USPS vacancy data. This dataset is created when postal carriers observe that a home has been vacant for 90 days and record it as such in the USPS's main address database (this data does not include short-term or seasonal vacancies). This prevents mail addressed to the vacant home from continuously being sorted into the route's load and carried back at the end of the day. The address database, including vacancy status, is routinely audited and maintained at an accuracy level above 95 percent. To further increase efficiency, the USPS makes this data commercially available to direct mailers. The companies can run their mailing lists through a software program that marks each record if the address is vacant. Mailings are not prepared for these addresses, so wasted printing and postage is avoided. The USPS provides this data to private contractors who sell subscription services. For our research purposes, we have subscribed to the vacancy data since April 2010. We run our list of Cuyahoga County addresses through the software, and create a panel of vacancy indicators.

For this analysis, we use the fourteen months of sales data that we have been able to link to complete vacancy data. This covers 10,878 sales in Cuyahoga County between April 1, 2010 and June 30, 2011.[14] We have attempted to exclude non-arms-length sales, starting by excluding

[13] Cuyahoga County makes its data available via Northeast Ohio Community and Neighborhood Data for Organizing (NEO CANDO). http://neocando.case.edu/cando/index.jsp

[14] At the time of this draft, we have been unable to overcome a software problem that is preventing us from counting

sales involving personal trusts and spouses. We exclude bulk purchases, where the price paid for a bundle of properties is recorded for each property in the transaction. In these cases, it is not clear what portion of the total prices should be related to the individual properties. We exclude sheriff sales in which a bank or federal agency repurchases a home on which it holds the mortgage. These prices reflect the lender's auction reserve rather than the market value of the home. The sales data are limited to single family homes. Multifamily buildings are counted in the vacancy, delinquency, and foreclosure counts. Buildings add zero or one to the counts, regardless of how many units they have. A multi-family building is considered vacant if less than 25 percent of its units are occupied. Apartments general pay taxes via one parcel number while condo parcels must be grouped by building to determine is the building has over 75 percent delinquent units, and thus adds to the delinquency counts of neighboring home sales.

3.1 Descriptive Statistics

Table 1 summarizes the monthly counts of distressed properties within the entire county. The sales data are entered into a geographic information system (GIS) and over-layered with the vacancy, delinquency, and foreclosure data. A 500-foot buffer is drawn around each sale. The seven types of distressed properties are counted and table 2 summarizes the counts. Note that delinquencies are the most common indicator of distress, with vacancy the next most common. The average home sells with 4 vacancies and 8 delinquencies within 500 feet. The average home sells with one recent foreclosure nearby. To place the counts in context, we need to think about the distribution of neighboring parcels. A home in low-density exurb may only have a handful of neighbors within 500 feet that could impact its value. In contrast, a home in the densest tract can have over 200 neighbors. The mean number of parcels in a home's 500 foot buffer is 98 and the standard deviation

the distressed properties for January sales. All the analyses exclude January 2011 observations. We will include them in future revisions of this paper. This should not change the results other than by increasing the sample size.

is 45.

Maps of one month's vacancies and median sales prices (figures 1 and 2) illustrate that the distribution of vacancies is different in low-price versus high-price areas. Maps of delinquencies and foreclosures have similar patterns. As we would expect, the counts of distressed homes are also correlated with one another. Tables 3, 4 and 5 illustrate both the overlap and the skewness of the distress data. Most of the observations of the counts are in the low single digits, and zeros are common. However, there are homes in distressed neighborhoods that are treated by very high counts of all types of distressed properties. The correlations in table 5 reinforce the need to control for all types of distress. Despite the positive correlations, individual treatments are significant in most of the models estimated below.

4 Results

In the first set of results presented in table 7, we see the hedonic price model with no spatial corrections, and two variations of the spatial model.[15] The coefficients on the counts of distressed properties are high in the estimate with no spatial correction, but we believe these are biased because the counts are correlated with unobserved disamenities of the immediate area around the home. For reasons discussed below, we will focus on the third model, with the spatial error correction, and refer to it as the main model.

In the main model, homes that have an additional vacant or vacant-delinquent home within 500 feet at the time of sale are selling for 1.4 percent less. The coefficient for homes that are only delinquent is similar, suggesting a 1.6 percent reduction for each additional distressed property.

[15] To calculate the estimates reported here, we use a recently released routine from StataCorp. The package, called *sppack*, creates spatial weight matrices and estimates spatial models using a maximum likelihood routine (Drukker, Peng, Prucha, and Raciborski 2011, Drukker, Prucha, and Raciborski 2011).

Tax-current recent foreclosures, whether occupied or vacant, do not display a significant impact in the corrected pooled estimates. If the recent foreclosure is tax delinquent (occupied or vacant), the main model estimates a negative impact close to 5 percent. These results are on the margin of significance. The negative impacts of homes that are only vacant or only delinquent appear small on a per-unit basis. We should keep in mind that the counts of vacancies and delinquencies are quite high. The implied reduction in the average home's price is 15 percent if we multiply the average vacant, delinquent and vacant-delinquent counts by the main model's coefficients.

4.1 Alternate Spatial Corrections

In specifying the spatial models, we use a weight matrix based on inverse distances up to one kilometer. Closer sales are given larger weights and further homes are down-weighted. The weights are row-normalized to sum to one, so the product of weight matrices and the price vector or error vector are all in the same units. In the results below, several other spatial corrections are presented and the consistency of the results gives us confidence that our weight matrices are reasonable and effective at removing the spatial autocorrelation bias.

In table 7, the λ and ρ values reflect the extent to which home prices are correlated with one another, or the extent the model's errors are geographically correlated. The ρ value in the spatial-error model is highly significant at .68. This coefficient is primarily of interest as a control, with the high, significant value suggesting that it is absorbing unobserved correlation between home prices and leading to coefficients on the treatment variables that can more plausibly be interpreted as causal. We report the ρs in the other models, without further discussion, for confirmation of the models' appropriateness. The log likelihood and χ^2 values suggest a spatial model with a spatially related error structure is a better fit to the data than a model assuming correlated prices with nearby sales. We will refer to the model with the error corrections as the main model, and we will report it in each table for ease of comparison. A full set of covariates for the main model is presented in table 19.

Table 8 presents the coefficients from the spatial error model (column 3 of table 7) and the marginal impacts that are calculated allowing for spatial feedback. If a distressed home decreases the price of a home, that home decreases the prices of homes nearby, and the prices of the homes nearby decrease the price of that home, then the coefficient from the model is understating the impact of an additional distressed home. The average direct treatment impact represents that percentage decrease in home prices if the decline is calculated to impact the neighboring home prices and then fed back into the original home sale observation (Drukker, Prucha, and Raciborski 2011). The change is calculated and averaged over all observations. We present these results simply to recognize that the coefficients are very slightly understating the impacts. The difference is one tenth of a percent or less and would be lost in rounding in most cases.

In table 7, we see that the spatial corrected models are quite different than the uncorrected model. Assuming that we have observed everything important about the homes, or that location does not matter, is not plausible. For comparison, we present several alternate spatial corrections in table 9. Clustering the errors on the census tract returns the coefficients from the uncorrected model with two counts, vacant-delinquencies and delinquent-foreclosures, losing their significance. Including a census tract indicator makes the coefficient on the delinquency counts decline. The vacant-delinquent count has no impact in this specification, but the vacant-delinquent-foreclosure count becomes significant. The negative externality of the vacant and vacant-delinquent-foreclosed homes shows through even when the analysis is limited to variation within census tracts.

The data can place each home in a jurisdiction, and it is reasonable to think the jurisdiction has important impacts on the home price. Thus, an indicator of the jurisdiction should capture a lot of important unobserved spatial heterogeneity. In Cuyahoga County, cities correspond to significant differences in property taxes and provide very different levels of city services. They are usually grouped with one or two similar cities into school districts. Property taxes and school districts are known to have large impacts on home values (Oates 1969, Downes and Zabel 2002). When city indicators are included in the model, the coefficient on delinquencies is larger, as it is in the uncorrected model. The estimated impact of vacant-delinquent homes remains the same but loses significance. The coefficient on delinquent-foreclosures is eliminated. Adding a city-specific time trend changes the results only slightly. Combining the city indicators with the spatial error correction returns results that are similar to the main model.

The choice between the models should be guided by considering which spatial correction best reflects the unobserved local amenities and disamenities. The distance-weighted correction may reflect something valuable about a sub-group of houses within a city or census tract, such as beach or freeway access. Larger geographic groupings may obscure these differences. On the other hand, city and tract designations reflect the sharp borders in taxes and school quality that can be found in the county. The one and two kilometer distance matrices reach across these borders. Finally, it should be noted that a quarter of the census tracts have fewer than five observed sales, so tract indicators are representing averages of small groups of homes.

4.2 Comparison to Previous Studies

In the pooled estimates, we are reporting impacts of four types of recently foreclosed homes with one positive coefficient, two negative coefficients, and only one being significant. Are these inconsistent with the findings that grouped around a 1 percent negative impact from a neighboring foreclosed home in previous studies discussed in section 1.1. We hypothesized that recent foreclosures that are vacant or tax delinquent would have a greater negative impact. Our results suggest that the negative externalities are driven by the foreclosures that are also tax delinquent. Mortgage servicers usually pay property taxes to prevent tax foreclosures. Therefore, the delinquent homes are likely in the hands of non-attentive investors who either plan to sell the home before the tax-foreclosure process starts, or are willing to let the lower value units of a bulk purchase be repossessed by the state. No doubt other studies would have found higher impacts for tax-delinquent foreclosures if they could identify them.

The large coefficeint on the delinquent-foreclosed homes also reflects a weak housing market, deep into the housing bust. In 2010 and 2011, Cuyahoga County had a very high inventory of homes for sale. Prices had been declining for several years and showed minimal indications of recovering. Home prices are usually sticky because sellers need to repay their mortgages and they anchor their perception of their home's value based on the price they paid. However, by 2010, many owners were capitulating and accepting lower prices. Most of the previous foreclosure impact studies were looking for lowering of values in markets with various upward pressures.

What could explain the counter intuitive finding that an occupied, tax-current recent foreclosure has no impact on neighboring sales? A key insight comes from decomposing the analysis by the poverty level or vacancy level of the census tract. In tables 12 and 13, we see that in higher-income and lower-vacancy neighborhoods, an occupied tax-current foreclosure has the impact one would expect, large and negative. This is likely working through the discount on homes sold out of REO and appraisers' selection of comparable properties during the appraisal process. The positive connection between foreclosure and sale prices is mainly in the high-poverty and high-vacancy neighborhoods. In these areas, banks may be only foreclosing on homes that retain some value because the foreclosure and REO processes are expensive. In these distressed areas, a foreclosed home being reoccupied is a positive sign. The occupancy may be serving as an indicator that the immediate area around that home is more desirable than other areas with similar levels of vacancy and delinquency. Cleveland proper lost 17 percent of its population in the last decade, with higher losses in the most distressed neighborhoods. In a "best of the worst" scenario, occupied homes on the street may signal to investors or home buyers that homes in that area have more value. This is consistent with anecdotal reports from community development practitoners and local policymakers.

One of the contributions we promised was to correct the estimate of the impact of foreclosures by taking into account other distressed properties in the neighborhood and properties with multiple indicators of distress. In table 10, we present the results of models estimated with each of the counts alone, and then with all three counts in one model. If vacancies, delinquencies or foreclosures are placed in the model alone, the coefficients are negative and significant. With all three non-exclusive counts in the model, the vacancy and delinquency impacts are reduced and the average impact of a foreclosure lands near zero.

It is common in the literature to report the results in several different distance buffers to demonstrate the rate of distance decay in the impact of the distressed property. Table 11 shows the results of estimating the model with two exclusive counts in a small (<250ft) and large (250-1000ft) buffer. The coefficients are larger in the smaller buffer for counts of vacant, delinquent, and vacant-delinquent homes.

4.3 Housing Submarkets

As can be seen through our foreclosure coefficients, it is helpful to think of the county as containing several separate housing markets which value vacancies, delinquencies, and foreclosures to different extents. To investigate this possibility, we separated the census tracts into three subsets by terciles of poverty, vacancy and density. The vacancy rate was calculated as the average ratio of vacancies to residential units over the year. The density is measured by the total geographic area of the tract divided by the number of residential units. Maps depicting each of the census tract categories can be found in figures 3 through 5.

The first results of the submarket models appear in table 12. An important item to note is the differences in sample size. The census tracts are divided at the 33rd and 66th percentiles of the distribution of poverty rates in the 465 census tracts. However, a higher share of the sales transactions in high-poverty areas are sheriff or bulk sales, and they are excluded from this analysis. The first important discovery here is that high-poverty census tracts are driving up the coefficients on the tax-current foreclosure counts. The results from the relatively large sample in low-poverty tracts look like a "normal" market: foreclosures have a large negative impact. In the high-poverty submarket, a home has a negative correlation with neighboring sale prices if its owner is not paying taxes, but it has a positive correlation with sale prices if the lender or servicer was not delinquent.

In the high-poverty tracts there are probably a couple forces at work. First the property values are now so low in many cases that they do not cover the cost of foreclosing. In many instances mortgage holders may be choosing to file for foreclosure on the properties that are in somewhat better condition or on slightly more desirable blocks. Likewise, buyers observe that once a home goes through foreclosure, it often remains vacant and neglected, as indicated by the delinquency. If the servicer purchases the home, pays the taxes, and sells it to someone who occupies it or attracts a rental tenant, this is a sign of hope for the nearby properties.

Dividing the data by low, medium, and high vacancy tracts parallels the poverty divisions (table 13). Again the observation count is smaller in the high-vacancy areas. Vacant, delinquent, foreclosed, vacant-delinquent and vacant-foreclosed homes all have large negative impacts in low-vacancy tracts. Vacant-delinquent-foreclosed properties have a large, marginally significant, negative impact in the high-vacancy submarket. Considering that we are using a distance-based measure of treatment, it is reasonable to think that price impacts could be different in areas with different density. A home in a dense area has more neighboring properties that could be distressed, and distressed neighbors are more visible. After dividing the data into low-, medium-, and high-density subsets, we see mixed results (table 14). In the dense tracks, the contrast of positive and negative coefficients on foreclosure counts, depending on tax status, is again visible. Distressed property counts in medium- and low-density areas return negative coefficients in all but one (insignificant) instance.

4.4 Non-Arm's Length Sales

As discussed in section 3, we excluded sales in which the lender was reclaiming a property used as collateral for a mortgage. Table 6 illustrates that sales involving institutions are a large part of this market. The percentages in the table are the share of all transactions involving the specified type of buyer or seller. Adding these institutional sales back into the dataset increases the number of observations by 18 percent. If we return those sales to the dataset, and estimate the model with an indicator for an institutional buyer or seller, we see that the treatment coefficients are very similar to those of the main model (table 15). An important thing we learn here is the magnitude of the discounts banks and federal agencies take and give in their transactions. When a bank or federal agency purchases a home at a sheriff sale, on average they set auction reserves 34 percent less than the price for an equivalent property in an ordinary sale. The discount for homes coming out of REO is even steeper, at 59-63 percent, suggesting the repossessors are taking losses in many cases. Investors, in sharp contrast, buy at a 55 percent discount and sell at above 86 percent of market price on average. For non-profits, the estimate returns the nonsensical coefficient of -1.77. This is because non-profit are given homes more often than they actually purchase them, and prices far outside the rest of the price distribution are recorded (such as $10 or $100).

4.5 Addressing Data Skewness

Table 16 contains the results of three estimates that address the fact that the counts of vacancies, delinquencies and vacant-delinquent homes are skewed. Most of the counts are below five, with a handful of homes being sold near 20, 60 or even 100 distressed properties. The first model includes a cubed form of each skewed measure, to allow for decreasing marginal impact at high levels. The second model uses an indicator for observations that are above the 95th percentile for any of the three counts. The indicator is interacted with the vacancy, delinquency, and vacancy-delinquency counts to allow for a different slope at high levels. The third model simply excludes the observations with the high counts. In all three alternatives, the estimated impacts of delinquent and vacant-delinquent homes increase. The impact of vacancy decreases only slightly in two of the variations. These results suggest it is safe to say that a few unusually high observations are not driving the results. If anything, the linear nature of the model is understating the impact of delinquencies and vacant-delinquencies because it is pooling observations with high counts and low marginal impacts along with the more numerous low-count-high-marginal impact observations.

5 Policy Implications

5.1 Removing Blight

Using our main model, we attempted a simple experiment to estimate the potential benefit from eliminating some of the distressed properties. We returned to our model and re-predict the sale prices seven times, each time setting the counts on one of the distressed property types to zero. We sum the increase in the predicted values and divide it by the average number of units with the marker of distress in a month. This gives a predicted per-unit increase in transaction values. The values are implicitly weighted by the sales activity the distressed properties actually influenced, but they suggest a proportional increase in property values of unsold homes as well. This benefit could be weighed against the cost of a program that alleviates distress on properties.

Table 18 presents the results of the experiment. To place the table in context, the total value of all home transactions in the dataset is $1.4 billion. In per-unit terms, foreclosure in combination with delinquency leads to the largest losses of value at $4,656 and $5,924. But the total values, before dividing by the units, tell a different story. The total value lost to sellers due to homes that are vacant, delinquent, or both is approximately $80 million.

If policy-makers set out to address all multiple-distress properties, they would have the daunting task of treating over 11,500 homes. Putting a laser focus on the approximately 450 homes that are foreclosed and delinquent seems more feasible. Recovering $2.3 million of value for sellers might not justify the expense of a program, but when the increased value of nearby homes is taken into consideration, the benefits would be much larger. A successful program would have the indirect effect of stabilizing the property tax base.

In this experiment, we are assuming a targeting by type of distress. For example, a program could help people with vacant-foreclosed homes rather than just vacant homes. In practice, the programs could be targeted geographically, by the type of neighborhood, or not at all. Targeting would have to take into account equity concerns because preventing a foreclosure in a neighborhood where homes sell for $300,000 may have a larger percentage and dollar benefit than preventing a foreclosure in a neighborhood with $5,000 homes, but such assistance is rarely targeted to high-income neighborhoods.

While it is simple in a dataset to remove vacancy or delinquency observations, designing a program to successfully eliminate these conditions in actual homes is very challenging. In the case of delinquency, policymakers should bear in mind that it is unlikely that property tax-delinquency itself that lowers property values, but rather the neglect associated with property tax-delinquency.

Forgiving delinquent property taxes does not change the fact that the homeowner is unable or unwilling to invest in his or her property. Likewise, eliminating vacancies in homes that are not candidates for demolition would require attracting migration to the region or stimulating household formation.

Finally, if lenders are strategically foreclosing on the few desirable properties in highly distressed areas, there is no easy way for policymakers to obtain the properties that are mortgaged and in default. In these cases lenders maintain their first-position security interests, which encumber properties and prevent redevelopment. In such cases, creative ways to encourage foreclosure or the surrender of the lenders' leans would need to be pursued before the property could be eliminated.

5.2 Housing Market Interventions

Since the foreclosure crisis began, state and federal governments have spent billions of dollars on various foreclosure prevention programs, in part to combat the negative externalities prior research has associated with foreclosure. Our research suggests that vacancy and abandonment in less robust housing markets should be receiving at least as much attention as foreclosures. Indeed, this has long been recognized by community development practitioners, who are often more concerned with the vacancy and abandonment that sometimes results from foreclosure than the foreclosures themselves.

Foreclosures are currently a serious problem across the United States, but they are not long-term problems like vacancy and abandonment. As the economy improves and borrowers are better able to service their debt, the number of foreclosures will drop. In the meantime, some foreclosures are quickly reoccupied by owners or purchased by an attentive landlord who rents the property out. Thus, not every prevented foreclosure will mitigate the externalities associated with vacancy and abandonment. But as long as policy remains focused on the construction of new housing over the maintenance of older ones, vacancy and abandonment will persist. To date, there have not been many policy responses aimed specifically at vacancy and abandonment, and most are untested.

For example, vacancy registration ordinances have arisen in municipalities across the United States. They usually require a property to be registered within a specific number of days of becoming vacant, and subject the property to additional housing code inspections while registered or at the point of sale. While they do not remediate distressed property, they may incentivize property owners to reoccupy vacant property to avoid registration, or to take better care of the property in light of the additional inspections. To date, there has been no research done on the effectiveness of these programs.

When combating vacancy and abandonment, modern land banking is one strategy that shows promise. Modern land banks are public or quasi-public entities charged with acquiring, remediating, and placing vacant and abandoned homes back into productive use (Fitzpatrick 2010). The most intriguing modern land banks are organized under Ohio law, with statutorily defined public missions, stable funding mechanisms, and significantly more power and flexibility than other modern and historic land banks. In less-robust markets like Genesee County, MI and Cuyahoga County, OH, land banks often focus upon the demolition and repurposing of older, distressed housing stock. Like studies of vacancy ordinances, evaluations of modern land banks have been very limited (Griswold and Norris 2007).

Finally, our results illustrate the difficult decisions that must be made when deciding how to allocate resources to combat vacancy and abandonment. It appears that the benefits of each marginal dollar spent on mitigating vacancy and abandonment would be highest in low-vacancy and low-poverty areas. However, the incidence of vacancy and abandonment is highest in high-vacancy and high-poverty areas. The question of whether to focus resources in low-poverty and low-vacancy areas in order to reap the largest immediate benefits or high-vacancy and high-poverty areas to address the largest manifestation of the problem does not have a clear answer.

6 Conclusions

Using our unique data on parcel-level vacancies, and incorporating tax delinquency data, we have a richer understanding of the impact of distressed properties. We can see that each type of distressed property has its own impact on the sale price of nearby homes. In medium- and low-poverty census tracts, homes that are vacant, delinquent or both have a negative impact between 1.5 and 3 percent for each additional distressed property within 500 feet of the sale. The impact of recent foreclosures is more complex than previous studies suggested. In low-poverty tracts, we find a large negative impact around 4 percent for recent foreclosures that are not tax delinquent. In high-poverty and high-vacancy areas, tax current foreclosures are, if anything, positively correlated with home sale prices. This could reflect selective foreclosure by lenders on homes that are in better condition or slightly better locations. Also the homes' tax-current state indicates that it's owner that has some financial resources and a desire to prevent a tax foreclosure. In contrast, tax-delinquent foreclosed homes have negative correlations with neighboring sale prices in most of the models estimated.

Homes that are vacant lower the surrounding property values, even if they have not been through a recent foreclosure and presumably have an attentive, tax-paying, owner. Given the high counts of vacant and delinquent homes, we estimate that these properties are doing more than foreclosures to lower surrounding property values. However, when it comes to policy responses, concentration on foreclosures with additional distress characteristics would return a far greater benefit per unit improved. The other half of the equation, the costs of improving a vacant or delinquent foreclosure, must be weighed once effective policies for eliminating the impact of these properties have been designed, measured, and tested.

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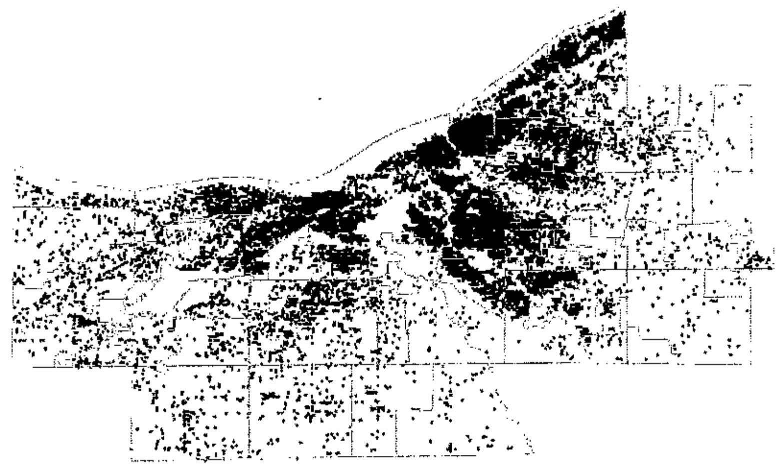

Figure 1: Vacancies in Cuyahoga County, June 2010.

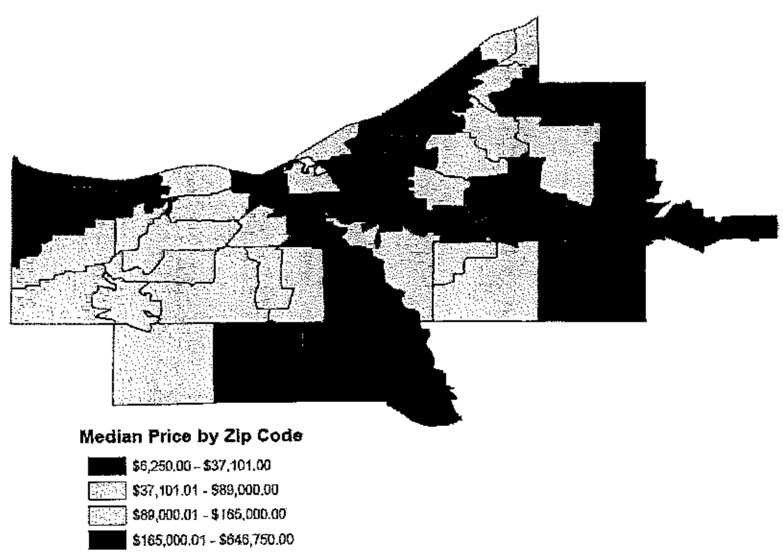

Figure 2: Home sale prices in Cuyahoga County, 2010.

Exclusive	Mean	SD	Min	Max
Vacancies	12,204	516	11,385	13,301
Delinquencies	36,726	227	36,319	37,207
Foreclosures	2,744	142	2,514	3,007
Vac and Del	9,650	322	9,235	10,252
Vac and For	1,898	131	1,558	2,011
Del and For	247	69	170	370
Vac, Del and For	197	53	133	291
Total	63,666	533	62,849	64,941
Non-exclusive	Mean	SD	Min	Max
Vacancies	23,950	734	22,434	25,776
Delinquencies	46,820	288	46,479	47,047
Foreclosures	5,087	159	4,856	5,414

Table 1: Descriptive Statistics - Monthly County-Wide Totals of Distressed Properties. In the exclusive figures, a distressed property is only counted in one category. In the non-exclusive figures, one property can contribute to multiple counts if it has multiple markers of distress.

	Mean	SD	Min	Max
Log Sale Price	11.212	1.282	1.946	14.701
Sale Price	127,688	137,001	7	2,425,000
Exclusive	Mean	SD	Min	Max
Vacancies	2.175	2.547	0	22
Delinquencies	5.966	7.983	0	52
Foreclosures	0.470	0.875	0	9
Vac and Del	1.682	4.219	0	65
Vac and For	0.383	0.755	0	6
Del and For	0.051	0.298	0	7
Vac, Del and For	0.041	0.206	0	2
Non-exclusive	Mean	SD	Min	Max
Vacancies	4.281	6.244	0	79
Delinquencies	7.739	11.583	0	109
Foreclosures	0.944	1.433	0	17

Table 2: Descriptive Statistics - Prices and Distress counts in 500 ft. Buffers around Sales. In the exclusive figures, a distressed property is only counted in one category. In the non-exclusive figures, one property can contribute to multiple counts if it has multiple markers of distress.

	Vacancies									
Delinquencies	0	1-10	11-20	21-30	31-40	41-50	51-60	61-70	71-80	Total
0	1,086	575	0	0	0	0	0	0	0	1,661
1-10	1,820	4,950	113	1	0	0	0	0	0	6,884
11-20	10	882	237	7	0	0	0	0	0	1,136
21-30	0	232	274	20	0	0	0	0	0	526
31-40	0	74	199	58	1	0	0	0	0	332
41-50	0	15	86	87	14	0	0	0	0	202
51-60	0	2	18	32	26	4	1	0	0	83
61-70	0	0	3	3	22	3	0	0	0	31
71-80	0	0	0	1	2	0	4	0	0	7
81-90	0	0	0	0	0	0	3	3	0	6
91-100	0	0	0	0	0	1	2	5	0	8
101-110	0	0	0	0	0	0	0	0	2	2
Total	2,916	6,730	930	209	65	8	10	8	2	10,878

Table 3: Frequencies of sales with each combination of counts.

	Foreclosures			
Vacancies	0	1-10	11-20	Total
0	2,601	315	0	2,916
1-10	3,176	3,545	9	6,730
11-20	93	836	1	930
21-30	11	197	1	209
31-40	6	59	0	65
41-50	0	8	0	8
51-60	0	10	0	10
61-70	1	7	0	8
71-80	0	2	0	2
Total	5,888	4,979	11	10,878

	Foreclosures			
Delinquencies	0	1-10	11-20	Total
0	1,487	174	0	1,661
1-10	4,046	2,838	0	6,884
11-20	205	922	9	1,136
21-30	81	445	0	526
31-40	42	289	1	332
41-50	20	181	1	202
51-60	4	79	0	83
61-70	2	29	0	31
71-80	0	7	0	7
81-90	1	5	0	6
91-100	0	8	0	8
101-110	0	2	0	2
Total	5,888	4,979	11	10,878

Table 4: Frequencies of sales with each combination of counts.

	Vacancies	Delinquencies	Foreclosures	Vac and Del	Vac and Fore	Del and For
Delinquencies	0.548					
	(0.000)					
Foreclosures	0.332	0.440				
	(0.000)	(0.000)				
Vac and Del	0.494	0.754	0.330			
	(0.000)	(0.000)	(0.000)			
Vac and For	0.382	0.311	0.265	0.238		
	(0.000)	(0.000)	(0.000)	(0.000)		
Del and For	0.083	0.145	0.235	0.099	0.113	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Vac, Del and For	0.157	0.146	0.062	0.160	0.124	0.016
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.104)

Table 5: Descriptive Statistics - Correlation between distress counts.

	Percent
Buyer - Bank	8.6
Buyer - Investor	9.0
Buyer - Non-Profit	0.7
Buyer - Federal Agency	4.2
Seller - Bank	8.0
Seller - Investor	9.6
Seller - Non-profit	1.1
Seller - Federal Agency	5.0

Table 6: Descriptive Statistics - Institutional Sales in the data before they are excluded. These are percentages of the 12,820 observed sales used in the estimates reported in table 15.

	Non Spatial	Spatial Lags	Spatial Errors (Main)
Vacancies	−0.023***	−0.015***	−0.014***
	(0.004)	(0.004)	(0.004)
Delinquencies	−0.026***	−0.021***	−0.016***
	(0.002)	(0.002)	(0.002)
Foreclosures	−0.010	0.001	−0.002
	(0.009)	(0.009)	(0.009)
Vac and Del	−0.015***	−0.011***	−0.014***
	(0.003)	(0.003)	(0.003)
Vac and For	−0.019+	−0.007	0.008
	(0.010)	(0.010)	(0.011)
Del and For	−0.003	−0.023	−0.047+
	(0.025)	(0.024)	(0.027)
Vac, Del and For	−0.088*	−0.078*	−0.049
	(0.035)	(0.034)	(0.034)
Property Char.	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes
Constant	11.154***	7.682***	11.013***
	(0.058)	(0.189)	(0.065)
λ		0.313***	
		(0.016)	
ρ			0.681***
			(0.024)
N	10,878	10,878	10,878
Log Likelihood		−11708.684	−11624.062
χ^2		5943.684	8512.269

Table 7: Hedonic Price Models with and without Spatial Autocorrelation Corrections. Notes: This table reports coefficients and standard errors, in parentheses, from ML regressions of home sale prices on counts of distressed properties within 500 feet. Data represent sales of single family homes in Cuyahoga County from April 2010 through June 2011. Data are from Cuyahoga County administrative records, the USPS, and the American Community Survey. Significance key: + for p<.1, * for p<.05, ** for p<.01, and *** for p<.001.

	Maximum Likelihood Coefficient	Average Direct Treatment Impact
Vacancies	-.014365	-.014658
Delinquencies	-.016344	-.016677
Foreclosures	-.001680	-.001714
Vac and Del	-.014188	-.014478
Vac and For	.008029	.008193
Del and For	-.046593	-.047543
Vac, Del and For	-.049306	-.050310

Table 8: Maximum Likelihood Hedonic Price Models. Notes: This table reports coefficients and standard errors, in parentheses, from regressions of home sale prices on counts of distressed properties within 500 feet. Data represent sales of single family homes in Cuyahoga County from April 2010 through June 2011. Data are from Cuyahoga County administrative records, the USPS, and the American Community Survey.

	Clustered on Tract	Tract Fixed Effect	City Fixed Effect	City FE & City Trend	City FE & Spatial Error	Main
Vacancies	−0.023***	−0.018***	−0.011*	−0.010+	−0.012***	−0.014***
	(0.006)	(0.004)	(0.006)	(0.006)	(0.004)	(0.004)
Delinquencies	−0.026***	−0.005*	−0.022***	−0.022***	−0.016***	−0.016***
	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Foreclosures	−0.010	0.003	−0.000	−0.000	0.002	−0.002
	(0.015)	(0.009)	(0.015)	(0.015)	(0.009)	(0.009)
Vac and Del	−0.015	0.003	−0.014	−0.014	−0.012***	−0.014***
	(0.012)	(0.004)	(0.011)	(0.011)	(0.003)	(0.003)
Vac and For	−0.019	0.008	0.008	0.009	0.013	0.008
	(0.014)	(0.011)	(0.014)	(0.014)	(0.010)	(0.011)
Del and For	−0.003	−0.026	−0.005	−0.004	−0.039	−0.047+
	(0.066)	(0.027)	(0.062)	(0.064)	(0.026)	(0.027)
Vac, Del and For	−0.088+	−0.062+	−0.057	−0.060	−0.057+	−0.049
	(0.046)	(0.034)	(0.044)	(0.043)	(0.034)	(0.034)
Trend (Month)				−0.009		
				(0.007)		
Property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Indicators		Tract	City	City	City	
City-specific Trends				Yes		
Constant	11.154***	11.545***	10.756***	10.821***	10.801***	11.013***
	(0.083)	(0.678)	(0.130)	(0.137)	(0.096)	(0.065)
ρ					0.531***	0.681***
					(0.033)	(0.024)

Table 9: Other Spatial Corrections Hedonic Price Models. Notes: This table reports coefficients and standard errors, in parentheses, from regressions of home sale prices on counts of distressed properties within 500 feet. N=10,878. Data represent sales of single family homes in Cuyahoga County from April 2010 through June 2011. Data are from Cuyahoga County administrative records, the USPS, and the American Community Survey. Significance key: + for p<.1, * for p<.05, ** for p<.01, and *** for p<.001.

	Vacancies	Delinquencies	Foreclosures	All
Vacancies	−0.021***			−0.006*
	(0.002)			(0.003)
Delinquencies		−0.017***		−0.014***
		(0.001)		(0.002)
Foreclosures			−0.020 * *	−0.000
			(0.006)	(0.006)
Property Characteristics	Yes	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes	Yes
Constant	10.929***	10.993***	10.833***	10.998***
	(0.066)	(0.064)	(0.068)	(0.064)
ρ	0.724***	0.686***	0.768***	0.685***
	(0.022)	(0.024)	(0.019)	(0.024)
N	10,878	10,878	10,878	10,878
Log Likelihood	−11665.451	−11632.251	−11716.089	−11629.623
χ^2	7941.976	8414.106	7383.448	8456.340

Table 10: Separate Distress Counts Hedonic Price Models. Notes: This table reports coefficients and standard errors, in parentheses, from ML regressions of home sale prices on counts of distressed properties within 500 feet. Data represent sales of single family homes in Cuyahoga County from April 2010 through June 2011. Data are from Cuyahoga County administrative records, the USPS, and the American Community Survey. Significance key: + for p<.1, * for p<.05, ** for p<.01, and *** for p<.001.

	Buffers	
Vacancies 0-250ft	−0.024 ∗∗	(0.008)
Delinquencies 0-250ft	−0.022∗∗∗	(0.005)
Foreclosures 0-250ft	−0.004	(0.018)
Vac and Del 0-250ft	−0.009	(0.008)
Vac and For 0-250ft	0.032	(0.022)
Del and For 0-250ft	0.018	(0.039)
Vac, Del and For 0-250ft	0.013	(0.063)
Vacancies 250-1000ft	−0.001	(0.002)
Delinquencies 250-1000ft	−0.005∗∗∗	(0.001)
Foreclosures 250-1000ft	−0.005	(0.005)
Vac and Del 250-1000ft	−0.004 ∗∗	(0.001)
Vac and For 250-1000ft	−0.009	(0.005)
Del and For 250-1000ft	0.003	(0.018)
Vac, Del and For 250-1000ft	−0.025	(0.019)
Property Characteristics	Yes	
Month Indicators	Yes	
Constant	11.070∗∗∗	(0.065)
ρ	0.655∗∗∗	(0.025)
N	10,878	
Log Likelihood	−11612.339	
χ^2	8894.486	

Table 11: Distance Decay Hedonic Price Models. Notes: This table reports coefficients and standard errors, in parentheses, from ML regressions of home sale prices on counts of distressed properties within 500 feet. Data represent sales of single family homes in Cuyahoga County from April 2010 through June 2011. Data are from Cuyahoga County administrative records, the USPS, and the American Community Survey. Significance key: + for p<.1, * for p<.05, ** for p<.01, and *** for p<.001.

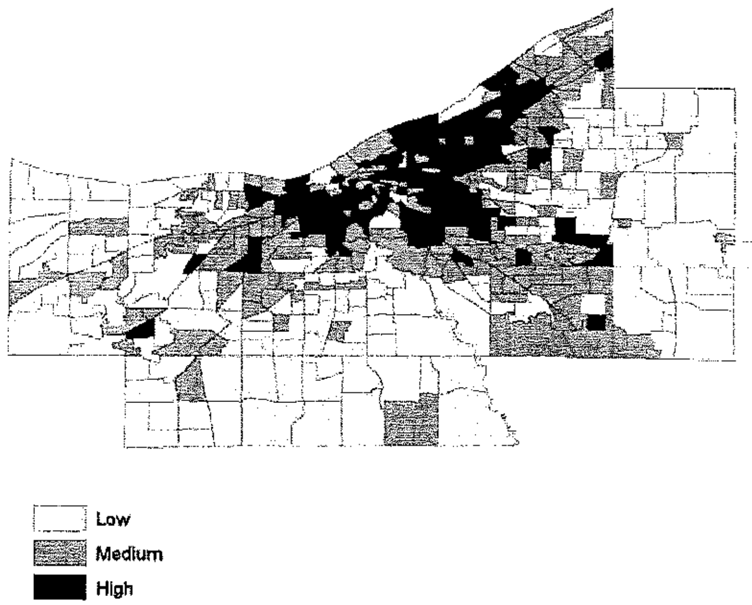

Figure 3: Census tracts by poverty.

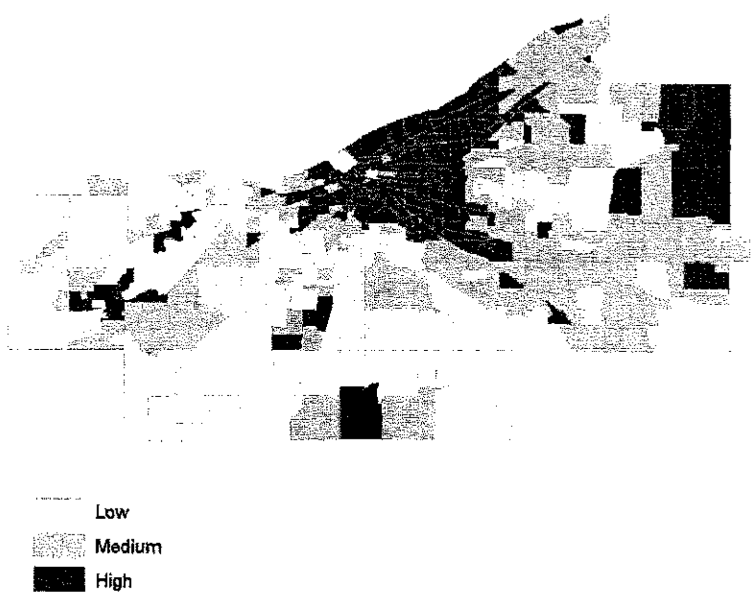

Figure 4: Census tract by vacancy rate.

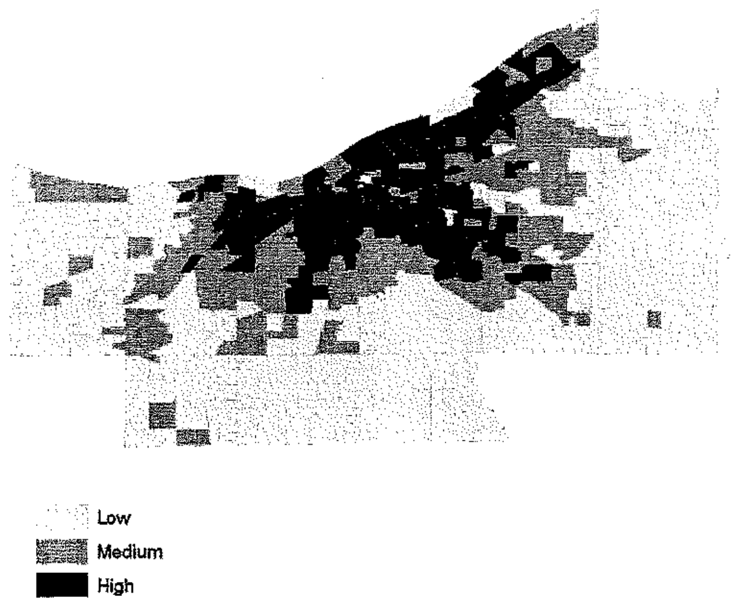

Figure 5: Census tract by density.

	High Poverty	Medium Poverty	Low Poverty	Main
Vacancies	−0.010	−0.019 * *	−0.015***	−0.014***
	(0.012)	(0.007)	(0.004)	(0.004)
Delinquencies	−0.007	−0.026***	−0.019***	−0.016***
	(0.005)	(0.004)	(0.003)	(0.002)
Foreclosures	0.020	−0.007	−0.040***	−0.002
	(0.026)	(0.017)	(0.011)	(0.009)
Vac and Del	−0.012+	−0.030***	−0.024*	−0.014***
	(0.006)	(0.008)	(0.010)	(0.003)
Vac and For	0.059+	0.004	−0.042***	0.008
	(0.033)	(0.017)	(0.012)	(0.011)
Del and For	−0.012	−0.108*	−0.031	−0.047+
	(0.060)	(0.055)	(0.040)	(0.027)
Vac, Del and For	−0.136	−0.055	0.020	−0.049
	(0.114)	(0.054)	(0.037)	(0.034)
Property Char.	Yes	Yes	Yes	Yes
Month Ind.	Yes	Yes	Yes	Yes
Constant	10.365***	10.915***	11.371***	11.013***
	(0.285)	(0.131)	(0.065)	(0.065)
ρ	0.400***	0.375***	0.613***	0.681***
	(0.064)	(0.047)	(0.025)	(0.024)
N	1,587	3,496	5,795	10,878
Log Likelihood	−2471.204	−4053.534	−2871.851	−11624.062
χ^2	818.508	2788.340	7741.138	8512.269

Table 12: Poverty Submarket Hedonic Price Models. Notes: This table reports coefficients and standard errors, in parentheses, from ML regressions of home sale prices on counts of distressed properties within 500 feet. Data represent sales of single family homes in Cuyahoga County from April 2010 through June 2011. Data are from Cuyahoga County administrative records, the USPS, and the American Community Survey. Significance key: + for p<.1, * for p<.05, ** for p<.01, and *** for p<.001.

	High Vacancy	Medium Vacancy	Low Vacancy	Main
Vacancies	0.000	−0.023***	−0.014 **	−0.014***
	(0.012)	(0.006)	(0.005)	(0.004)
Delinquencies	−0.008+	−0.020***	−0.018***	−0.016***
	(0.005)	(0.003)	(0.003)	(0.002)
Foreclosures	0.008	0.007	−0.039***	−0.002
	(0.027)	(0.014)	(0.011)	(0.009)
Vac and Del	−0.006	−0.035***	−0.057***	−0.014***
	(0.006)	(0.009)	(0.013)	(0.003)
Vac and For	0.059	−0.013	−0.031*	0.008
	(0.037)	(0.014)	(0.013)	(0.011)
Del and For	−0.042	−0.063	0.004	−0.047+
	(0.064)	(0.045)	(0.042)	(0.027)
Vac, Del and For	−0.184+	0.026	−0.004	−0.049
	(0.102)	(0.050)	(0.042)	(0.034)
Property Char.	Yes	Yes	Yes	Yes
Month Ind.	Yes	Yes	Yes	Yes
Constant	10.375***	11.038***	11.177***	11.013***
	(0.251)	(0.100)	(0.065)	(0.065)
ρ	0.420***	0.353***	0.550***	0.681***
	(0.058)	(0.042)	(0.031)	(0.024)
N	1,703	4,101	5,074	10,878
Log Likelihood	−2639.251	−4422.328	−2458.129	−11624.062
χ^2	1267.949	3995.935	6397.466	8512.269

Table 13: Vacancy Submarket Hedonic Price Models. Notes: This table reports coefficients and standard errors, in parentheses, from ML regressions of home sale prices on counts of distressed properties within 500 feet. Data represent sales of single family homes in Cuyahoga County from April 2010 through June 2011. Data are from Cuyahoga County administrative records, the USPS, and the American Community Survey. Significance key: + for p<.1, * for p<.05, ** for p<.01, and *** for p<.001.

	High Density	Medium Density	Low Density	Main
Vacancies	−0.013	−0.010+	−0.019 **	−0.014***
	(0.008)	(0.005)	(0.007)	(0.004)
Delinquencies	−0.009 **	−0.032***	−0.015***	−0.016***
	(0.003)	(0.003)	(0.005)	(0.002)
Foreclosures	0.019	−0.008	−0.056 **	−0.002
	(0.017)	(0.014)	(0.019)	(0.009)
Vac and Del	−0.011*	−0.051***	−0.046***	−0.014***
	(0.005)	(0.009)	(0.011)	(0.003)
Vac and For	0.029	−0.028+	−0.005	0.008
	(0.020)	(0.014)	(0.026)	(0.011)
Del and For	−0.046	−0.136 **	0.115	−0.047+
	(0.044)	(0.048)	(0.073)	(0.027)
Vac, Del and For	−0.067	−0.071	−0.012	−0.049
	(0.068)	(0.044)	(0.070)	(0.034)
Property Char.	Yes	Yes	Yes	Yes
Month Ind.	Yes	Yes	Yes	Yes
Constant	10.723***	11.195***	11.403***	11.013***
	(0.148)	(0.096)	(0.081)	(0.065)
ρ	0.524***	0.487***	0.485***	0.681***
	(0.049)	(0.043)	(0.030)	(0.024)
N	3,229	4,083	3,566	10,878
Log Likelihood	−4608.142	−3513.475	−1650.443	−11624.062
χ^2	1393.488	3625.672	5535.914	8512.269

Table 14: Density Submarket Hedonic Price Models. Notes: This table reports coefficients and standard errors, in parentheses, from ML regressions of home sale prices on counts of distressed properties within 500 feet. Data represent sales of single family homes in Cuyahoga County from April 2010 through June 2011. Data are from Cuyahoga County administrative records, the USPS, and the American Community Survey. Significance key: + for p<.1, * for p<.05, ** for p<.01, and *** for p<.001.

	Institutional		Main	
Vacancies	−0.014***	(0.004)	−0.014***	(0.004)
Delinquencies	−0.017***	(0.002)	−0.016***	(0.002)
Foreclosures	0.003	(0.009)	−0.002	(0.009)
Vac and Del	−0.015***	(0.003)	−0.014***	(0.003)
Vac and For	0.020*	(0.010)	0.008	(0.011)
Del and For	−0.053*	(0.025)	−0.047+	(0.027)
Vac, Del and For	−0.058+	(0.032)	−0.049	(0.034)
Buyer - Bank	−0.442***	(0.025)		
Buyer - Investor	−0.554***	(0.025)		
Buyer - Non-Profit	−1.770***	(0.081)		
Buyer - Federal Agency	−0.343***	(0.034)		
Seller - Bank	−0.634***	(0.025)		
Seller - Investor	−0.135***	(0.024)		
Seller - Non-profit	−0.280***	(0.065)		
Seller - Federal Agency	−0.590***	(0.031)		
Property Characteristics	Yes		Yes	
Month Indicators	Yes		Yes	
Constant	10.891***	(0.061)	11.013***	(0.065)
ρ	0.641***	(0.025)	0.681***	(0.024)
N	12,820		10,878	
Log Likelihood	−14430.475		−11624.062	
χ^2	10415.358		8512.269	

Table 15: Institutional-Sales-Included Hedonic Price Models. Notes: This table reports coefficients and standard errors, in parentheses, from ML regressions of home sale prices on counts of distressed properties within 500 feet. Data represent sales of single family homes in Cuyahoga County from April 2010 through June 2011. Data are from Cuyahoga County administrative records, the USPS, and the American Community Survey. Significance key: + for p<.1, * for p<.05, ** for p<.01, and *** for p<.001.

	Squares	Indicator & Interactions	Trimmed	Main
Vacancies	−0.023 ∗ ∗	−0.013∗	−0.012∗	−0.014∗∗∗
	(0.007)	(0.005)	(0.005)	(0.004)
Delinquencies	−0.032∗∗∗	−0.020∗∗∗	−0.022∗∗∗	−0.016∗∗∗
	(0.004)	(0.003)	(0.002)	(0.002)
Foreclosures	−0.000	−0.002	−0.005	−0.002
	(0.009)	(0.009)	(0.010)	(0.009)
Vac and Del	−0.059∗∗∗	−0.054∗∗∗	−0.055∗∗∗	−0.014∗∗∗
	(0.005)	(0.007)	(0.007)	(0.003)
Vac and For	0.015	0.012	−0.005	0.008
	(0.010)	(0.011)	(0.010)	(0.011)
Del and For	−0.045+	−0.045+	0.002	−0.047+
	(0.026)	(0.027)	(0.027)	(0.027)
Vac, Del and For	−0.041	−0.046	0.038	−0.049
	(0.034)	(0.034)	(0.034)	(0.034)
Vacancies^2	0.001+			
	(0.001)			
Delinquencies^2	0.001∗∗∗			
	(0.001)			
(Vac and Del)^2	0.001∗∗∗			
	(0.000)			
High		−0.540∗∗∗		
		(0.087)		
High*Vacancies		0.021∗		
		(0.009)		
High*Delinquencies		0.012∗∗∗		
		(0.004)		
High*(Vac and Del)		0.042∗∗∗		
		(0.008)		
Property Characteristics	Yes	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes	Yes
Constant	11.123∗∗∗	11.086∗∗∗	11.095∗∗∗	11.013∗∗∗
	(0.064)	(0.064)	(0.061)	(0.065)
ρ	0.621∗∗∗	0.632∗∗∗	0.619∗∗∗	0.618∗∗∗
	(0.027)	(0.027)	(0.026)	(0.024)
N	10,878	10,878	9,839	10,878
Log Likelihood	−11555.656	−11586.544	−9216.712	−11624.062
χ^2	9557.298	9208.930	9171.304	8512.269

Table 16: Extreme Value Robustness Checks. Notes: This table reports coefficients and standard errors, in parentheses, from ML regressions of home sale prices on counts of distressed properties within 500 feet. Data represent sales of single family homes in Cuyahoga County from April 2010 through June 2011. Data are from Cuyahoga County administrative records, the USPS, and the American Community Survey. Significance key: + for p<.1, * for p<.05, ** for p<.01, and *** for p<.001.

	Border Indicator	No Border Tracts	No Covariates	Levels	Main
Vacancies	-0.014***	-0.013**	-0.035***	-1041.774**	-0.014***
	(0.004)	(0.004)	(0.005)	(371.173)	(0.004)
Delinquencies	-0.016***	-0.016***	-0.047***	-386.602*	-0.016***
	(0.002)	(0.002)	(0.002)	(184.776)	(0.002)
Foreclosures	-0.002	0.002	-0.023*	-1393.718	-0.002
	(0.009)	(0.010)	(0.011)	(902.419)	(0.009)
Vac and Del	-0.014***	-0.013***	-0.028***	176.465	-0.014***
	(0.003)	(0.003)	(0.004)	(305.700)	(0.003)
Vac and For	0.008	0.017	-0.016	-674.838	0.008
	(0.011)	(0.011)	(0.013)	(1012.729)	(0.011)
Del and For	-0.047+	-0.048+	-0.099**	-1423.193	-0.047+
	(0.027)	(0.029)	(0.033)	(2576.731)	(0.027)
Vac, Del and For	-0.050	-0.052	-0.071+	751.601	-0.049
	(0.034)	(0.037)	(0.040)	(3269.663)	(0.034)
Border Tract	0.0769*				
	(0.032)				
Property Char.	Yes	Yes	Yes	Yes	Yes
Month Ind.	Yes	Yes	Yes	Yes	Yes
Constant	11.012***	10.972***	11.666***	67970.521***	11.013***
	(0.065)	(0.072)	(0.107)	(6611.676)	(0.065)
ρ	0.679***	0.690***	0.922***	0.705***	0.681***
	(0.024)	(0.027)	(0.011)	(0.023)	(0.024)
N	10,878	9,162	10,878	10,878	10,878
Log Likelihood	-11621.692	-10190.367	-13617.384	-136423.870	-11624.062
χ^2	8558.801	6541.542	1370.807	16417.560	8512.269

Table 17: Alternate Hedonic Price Models. Notes: This table reports coefficients and standard errors, in parentheses, from ML regressions of home sale prices on counts of distressed properties within 500 feet. Data represent sales of single family homes in Cuyahoga County from April 2010 through June 2011. Data are from Cuyahoga County administrative records, the USPS, and the American Community Survey. Significance key: + for p<.1, * for p<.05, ** for p<.01, and *** for p<.001.

	Benefit to Sellers	Average Units Per Month	Per Unit Benefit
Vacancies	$20,509,640	12,204	$1,681
Delinquencies	$52,647,470	36,726	$1,434
Foreclosures	$447,693	2,744	$163
Vac and Del	6,875,717	9,650	$712
Vac and For	-$1,713,677	1,898	-$903
Del and For	$1,148,880	247	$4,656
Vac, Del and For	$1,167,746	197	$5,924

Table 18: Policy Simulation. "Benefit to sellers" is the sum of the differences between the predicted prices from the main model (table 7, column three) using the original data and using data with the row-labeled type of distressed-home counts set to zero.

Main	Coef	SE
Vacancies	−0.014***	(0.004)
Delinquencies	−0.016***	(0.002)
Foreclosures	−0.002	(0.009)
Vac and Del	−0.014***	(0.003)
Vac and For	0.008	(0.011)
Del and For	−0.047+	(0.027)
Vac, Del and For	−0.049	(0.034)
Status at Sale - Vacant	−0.150***	(0.018)
Status at Sale - Delinquent	−0.284***	(0.031)
Status at Sale - Foreclosed	−0.482***	(0.032)
Status at Sale - Vac and Del	−0.678***	(0.032)
Status at Sale - Vac and For	−0.612***	(0.024)
Status at Sale - Del and For	−0.748***	(0.099)
Status at Sale - Vac, Del and For	−0.692***	(0.066)
Deck	0.078***	(0.018)
Open porch	0.030+	(0.016)
Enclosed Porch	0.029	(0.018)
Fireplace	0.056 **	(0.019)
Pre-1910	−0.435***	(0.043)
1910-1919	−0.331***	(0.040)
1920-1929	−0.232***	(0.031)
1930-1939	−0.113 **	(0.037)
1940-1949	−0.089***	(0.026)
1960-1969	0.046	(0.029)
1970-1979	−0.057	(0.041)
1980-1989	0.022	(0.047)
1990-1999	0.192***	(0.045)
2000-2009	0.424***	(0.051)
Condition fair	−0.325***	(0.029)
Condition good	0.003	(0.020)
Condition poor	−0.467***	(0.059)
Condition very good	0.117 **	(0.044)
Construction A	0.171***	(0.052)
Construction A+	0.384***	(0.057)
Construction B	0.033	(0.027)
Construction B+	0.043	(0.031)
Construction C	−0.020	(0.019)
Construction D	−0.100	(0.067)

Continued on next page

Table 19 – continued from previous page		
Exterior brick	0.069+	(0.038)
Exterior wood	−0.021	(0.037)
Exterior other	0.000	(0.035)
Radiator heat	0.074*	(0.030)
Other heat	0.041	(0.058)
Rooms four	−0.122 **	(0.041)
Rooms five	−0.017	(0.022)
Rooms seven	0.033	(0.021)
Rooms eight	0.072*	(0.029)
Rooms nine+	0.118 **	(0.038)
Baths two	0.101***	(0.023)
Baths three+	0.297***	(0.045)
Bedrooms two	−0.112***	(0.025)
Bedrooms four	−0.027	(0.022)
Bedrooms five+	−0.035	(0.047)
Central Air	0.029+	(0.017)
Halfbath one	0.081***	(0.019)
Halfbath two+	0.154***	(0.046)
Garage 1 attached	0.159***	(0.042)
Garage 2 attached	0.288***	(0.039)
Garage 3+ attached	0.430***	(0.059)
Garage 1 detached	0.120***	(0.032)
Garage 2 detached	0.225***	(0.031)
Garage 3+ detached	0.342***	(0.072)
Attic finished	0.051	(0.036)
Attic unfinished	0.067 **	(0.024)
Style Cape Cod	−0.028	(0.023)
Style other	−0.051+	(0.028)
Style ranch	−0.067*	(0.027)
Lot small	−0.096***	(0.021)
Lot large	−0.011	(0.023)
% Poverty (Tract)	−0.009***	(0.001)
% College Graduate (Tract)	0.013***	(0.001)
April 2010	0.029	(0.035)
May 2010	0.074*	(0.035)
June 2010	0.038	(0.034)
July 2010	0.070+	(0.039)
August 2010	0.013	(0.038)
October 2010	0.022	(0.040)
November 2010	0.008	(0.040)
December 2010	0.002	(0.040)
February 2011	−0.129 **	(0.042)
March 2011	−0.104 **	(0.038)
April 2011	−0.069+	(0.037)
May 2011	−0.016	(0.037)
June 2011	−0.041	(0.036)
Constant	11.013***	(0.065)
ρ	0.681***	(0.024)
N	10,878	
Log Likelihood	−11624.062	
χ^2	8512.269	

Table 19: Main Hedonic Price Models. Notes: This table reports coefficients and standard errors, in parentheses, from ML regressions of home sale prices on counts of distressed properties within 500 feet. Data represent sales of single family homes in Cuyahoga County from April 2010 through June 2011. Data are from Cuyahoga County administrative records, the USPS, and the American Community Survey. Significance key: + for p<.1 * for p<.05, ** for p<.01, and *** for p<.001.